SMASH
machine learning for science and humanities postdoctoral program

Jožef Stefan Institute

I FEEL SLOVENIA

Co-funded by the European Union

ANOMALY DETECTION WITH NORMALIZING FLOWS FOR MODEL-AGNOSTIC NEW PHYSICS SEARCHES

Rafał Masełek

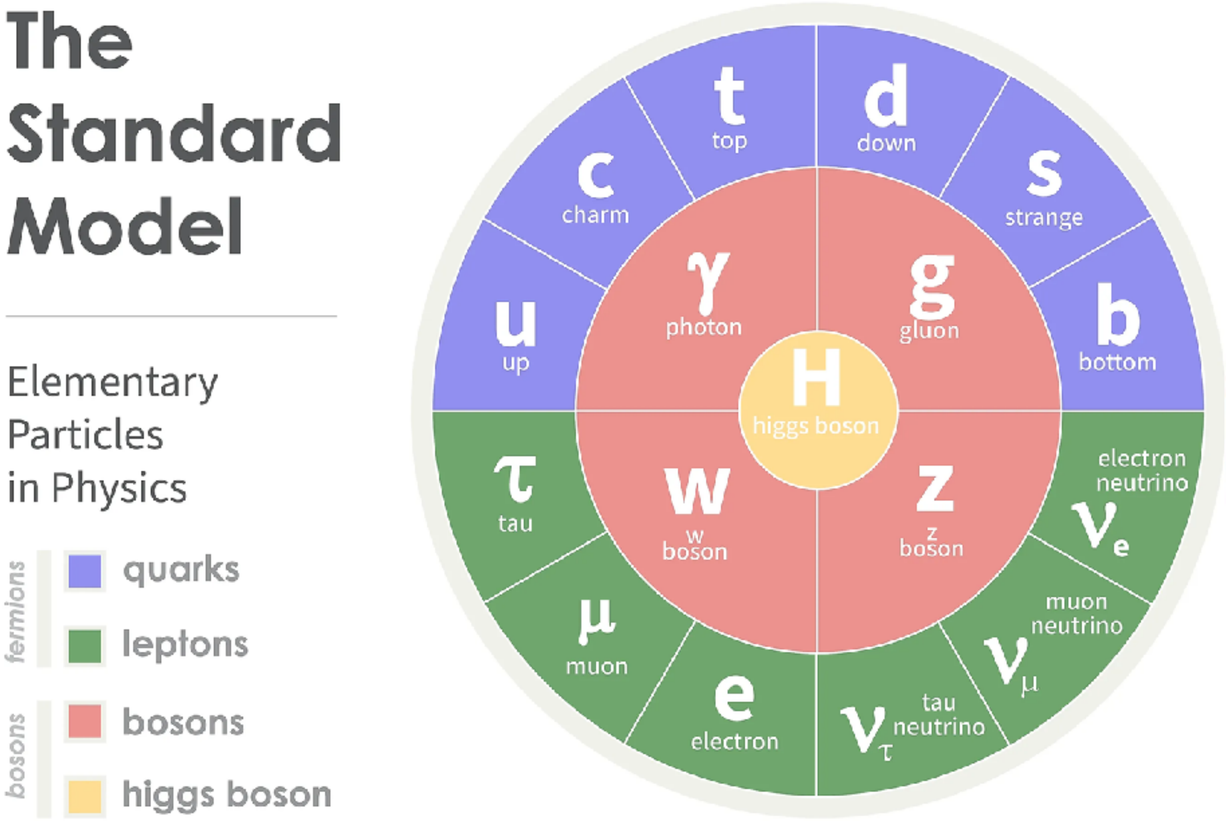
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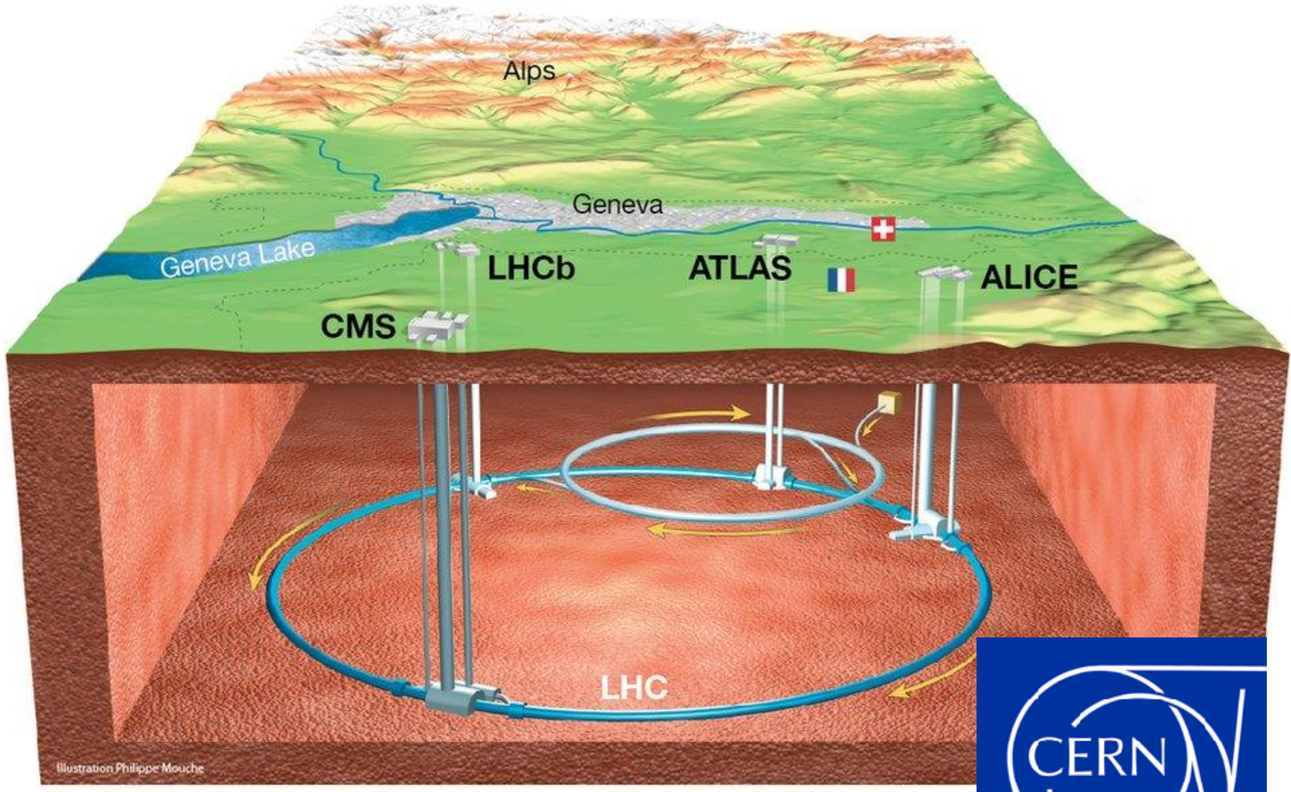
Sabine Kraml, Kazuki Sakurai & David Shih

2nd SMASHing workshop — 20-10-2026

This project has received the funding from the European Union's Horizon Europe research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 101081355. The operation (SMASH project) is co-funded by the Republic of Slovenia and the European Union from the European Regional Development Fund.

Quest for discovery of new particles

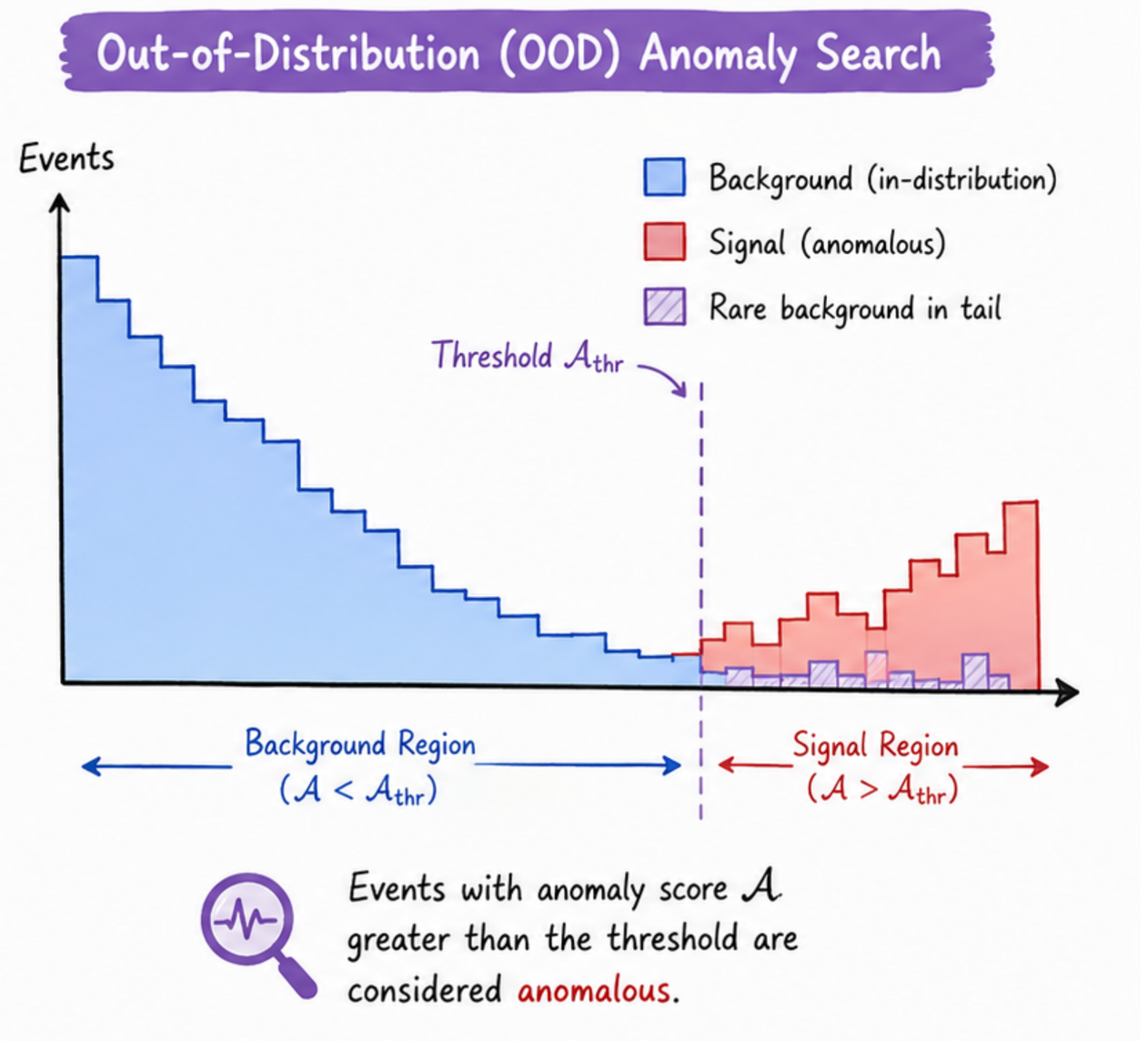




img source: Google Image

Anomaly searches in HEP

- Construct anomaly score A
  - SM background samples have small A
  - New physics signal samples have large A
- Select a threshold: A_{thr}
- Define the signal region as $A > A_{thr}$

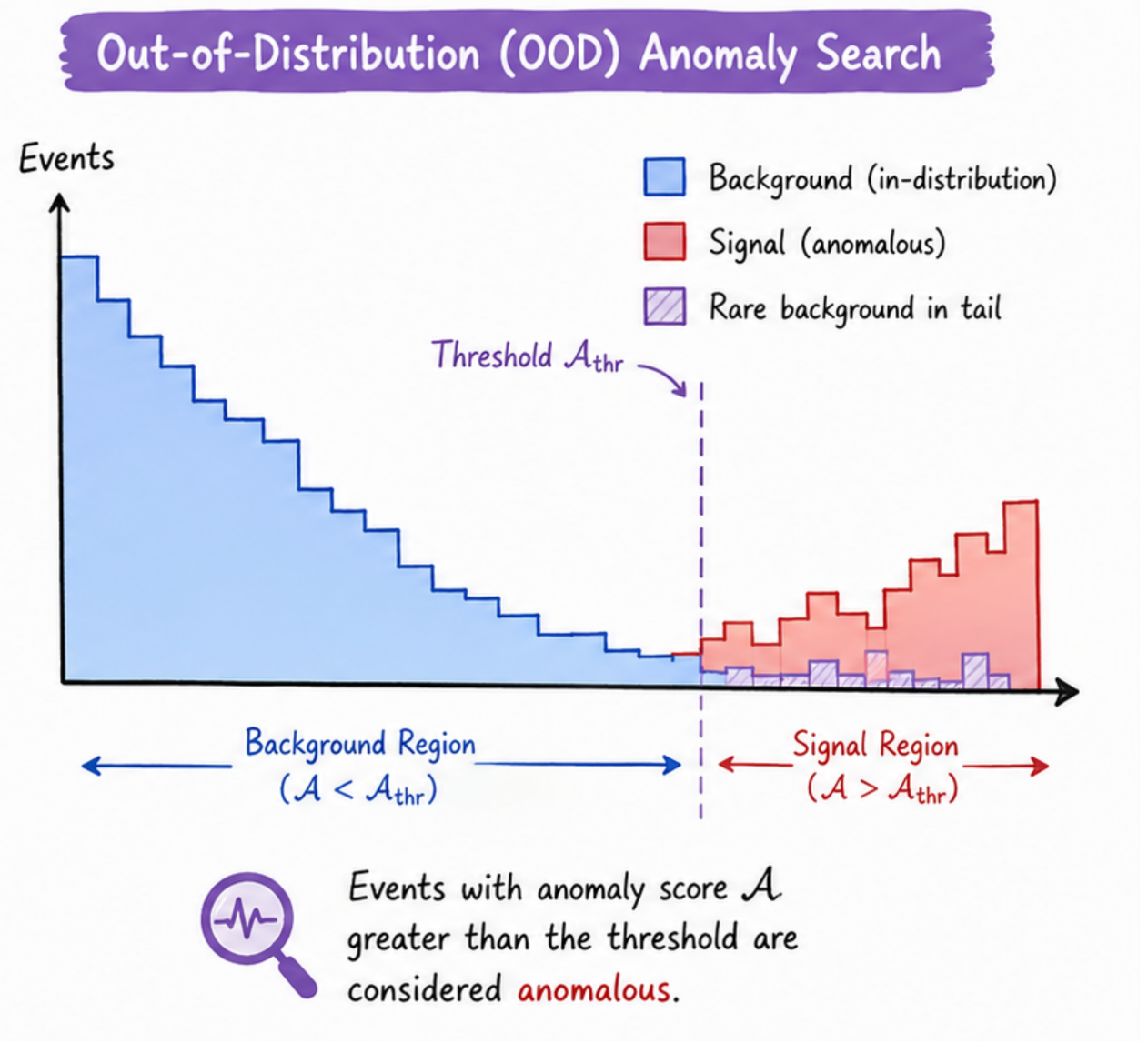


Anomaly searches in HEP

How?

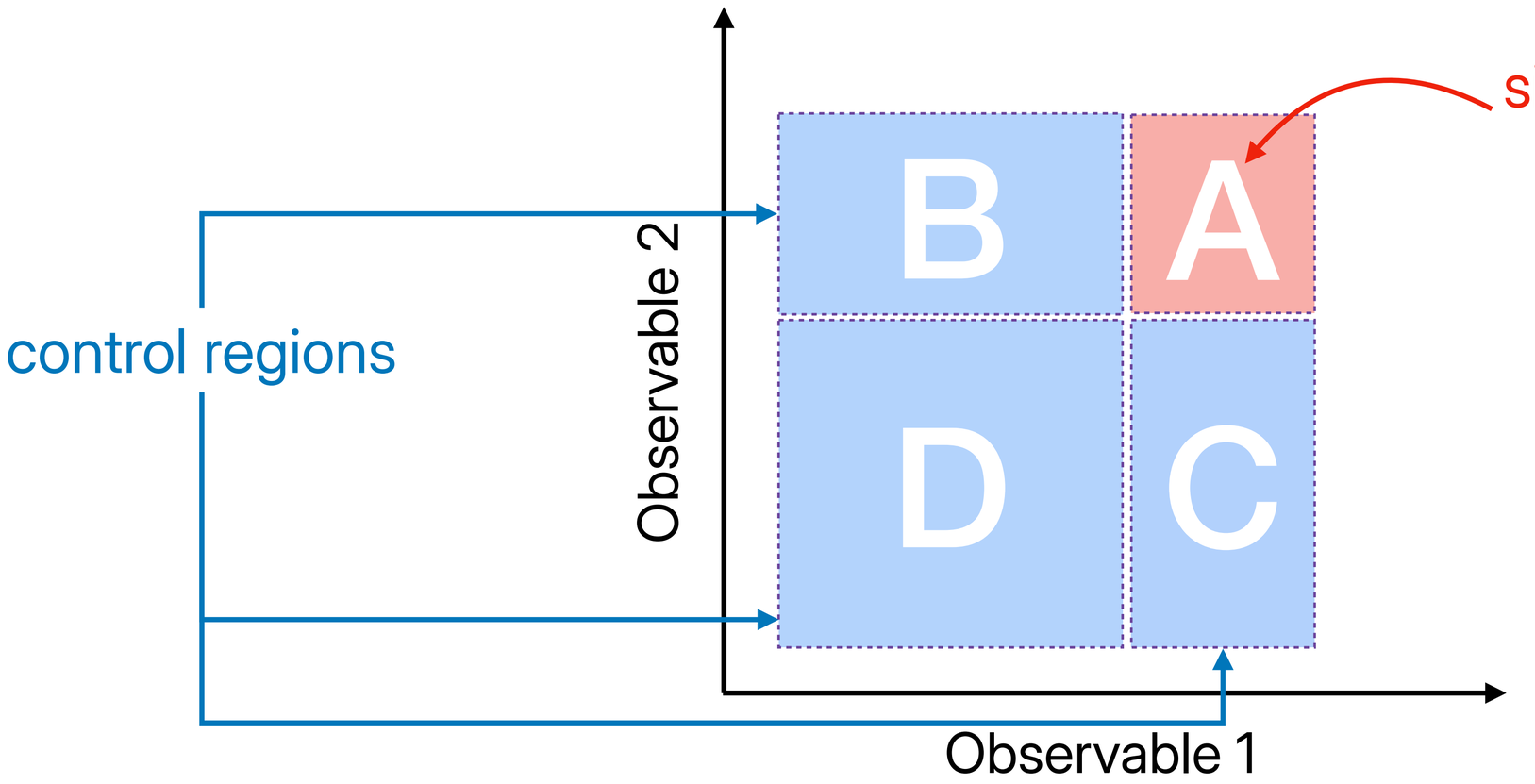
- Construct anomaly score *A*
  - SM *b*ackground samples have small *A*
  - New physics signal samples have large *A*
- Select a threshold: A_{thr}
- Define the signal region as A> A_{thr}

What about background in the signal region?



ABCD matrix method

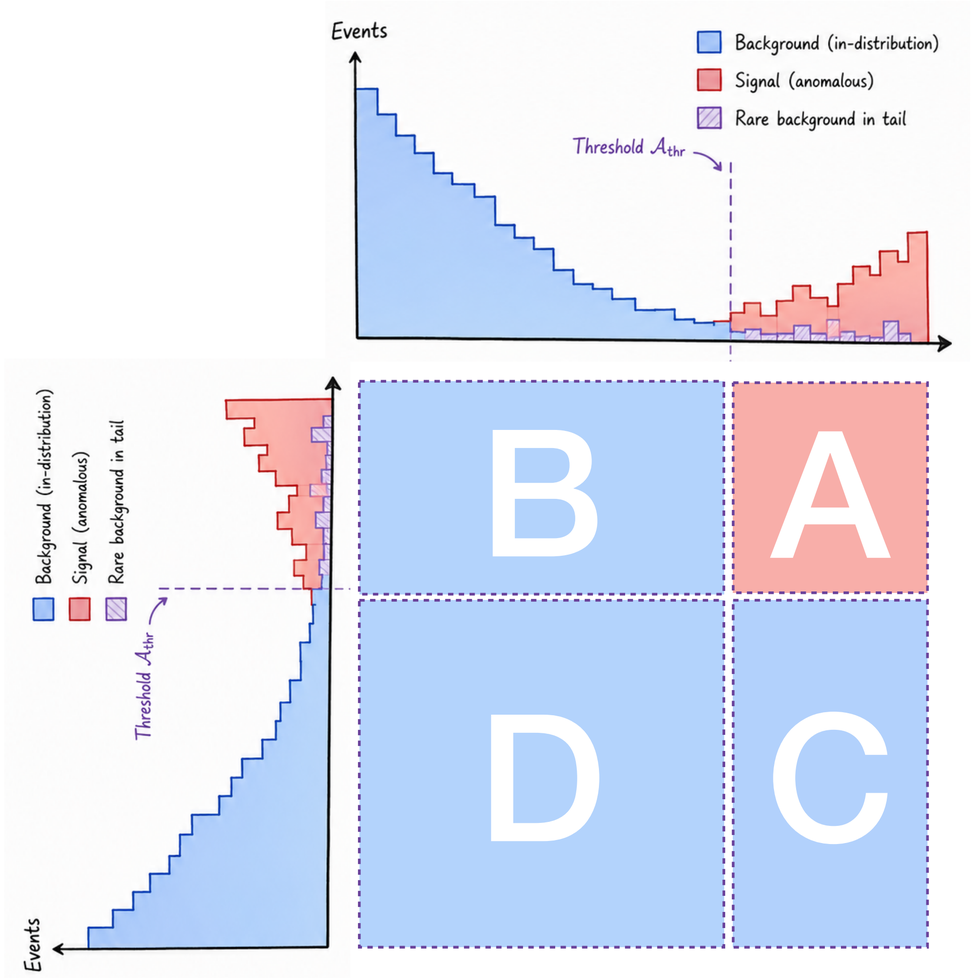
Established method for data-driven background estimation



$$N_A^{\text{bkg}} = N_B^{\text{bkg}} \frac{N_C^{\text{bkg}}}{N_D^{\text{bkg}}}$$

ABCD matrix method

Established method for data-driven background estimation

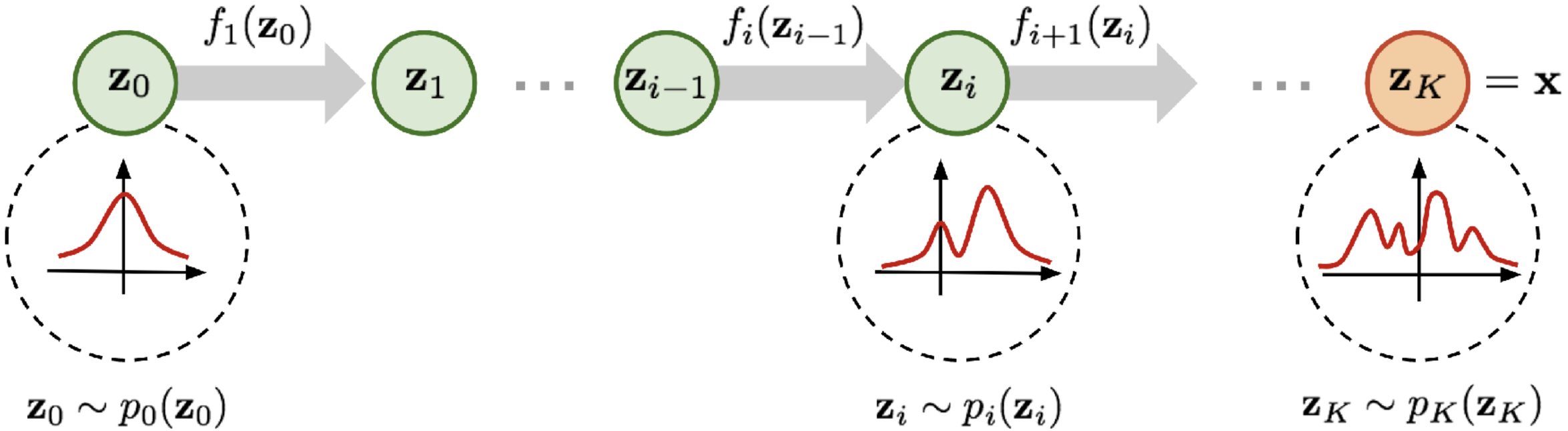


$$N_A^{\text{bkg}} = N_B^{\text{bkg}} \frac{N_C^{\text{bkg}}}{N_D^{\text{bkg}}}$$

Both anomaly scores have to be independent!

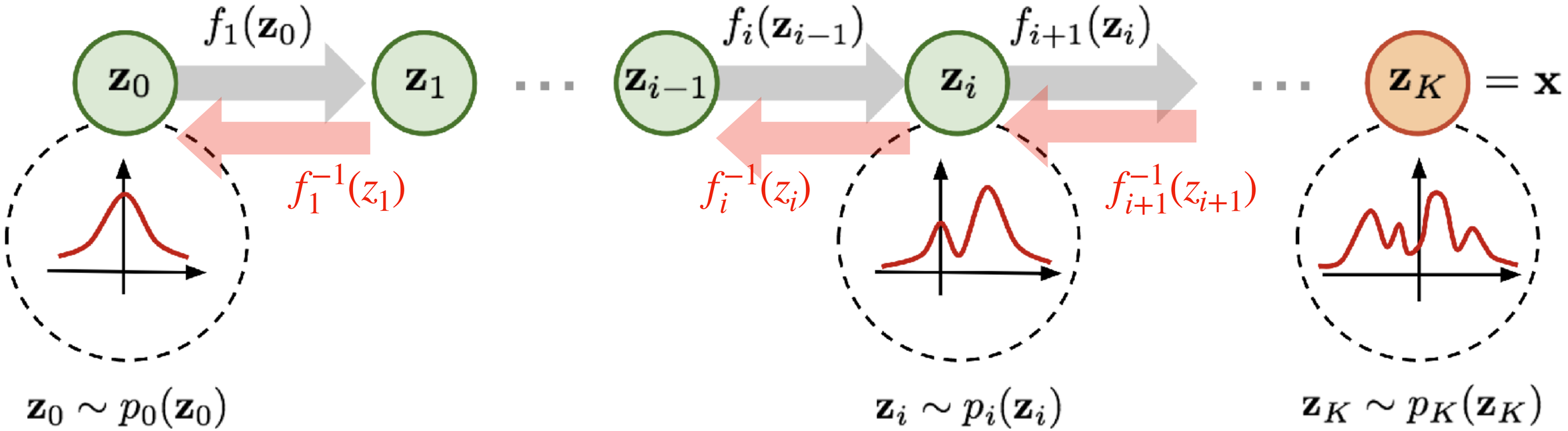
Relevant past works:
→ Kasieczka, Nachman, Schwartz, Shih [2007.14400]
→ Mikuni, Nachman, Shih [2111.06417]

Normalizing Flows



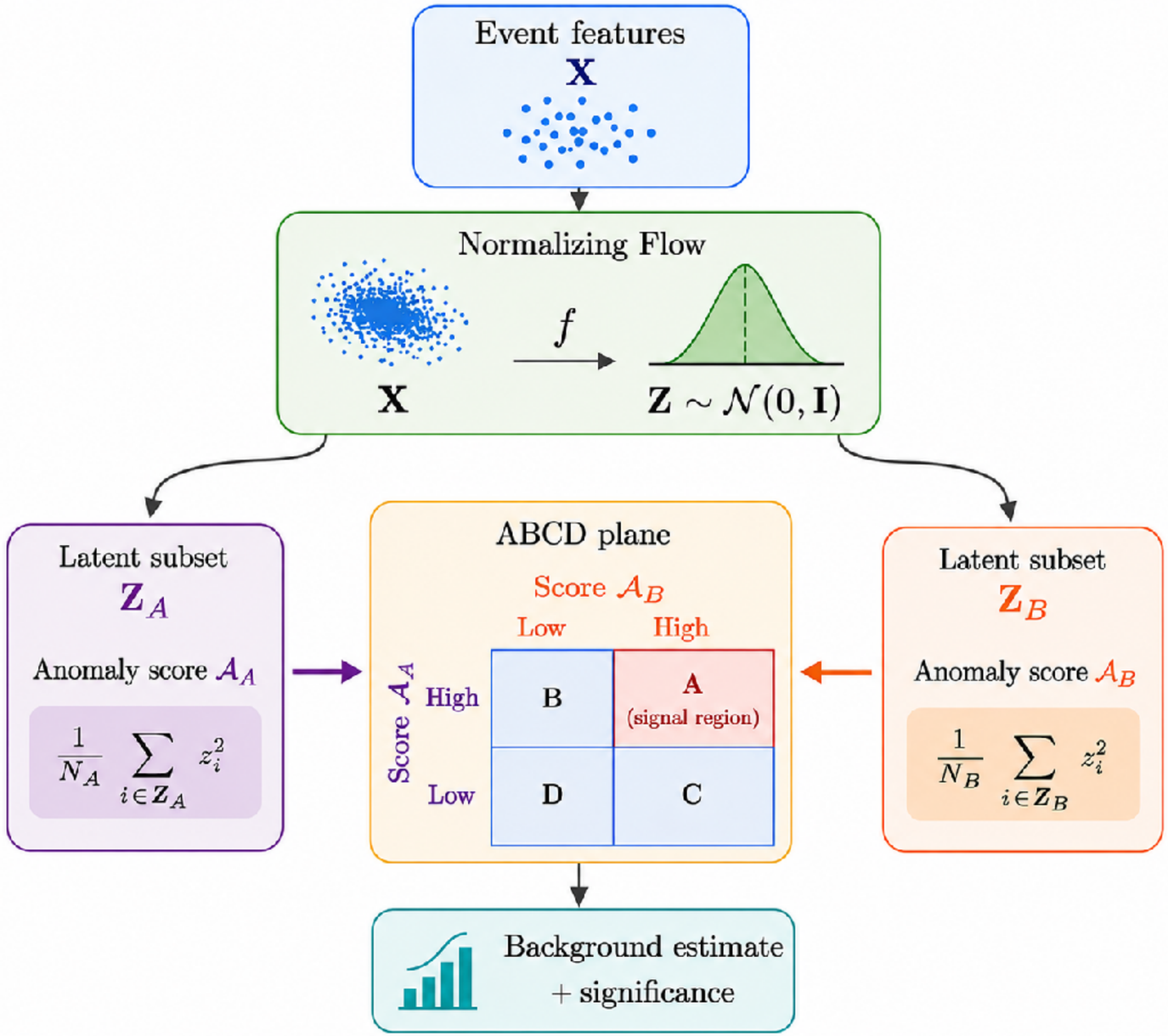
We build a sequence of invertible parametrisable functions that transform a multivariate Gaussian distribution to data distribution.

Normalizing Flows

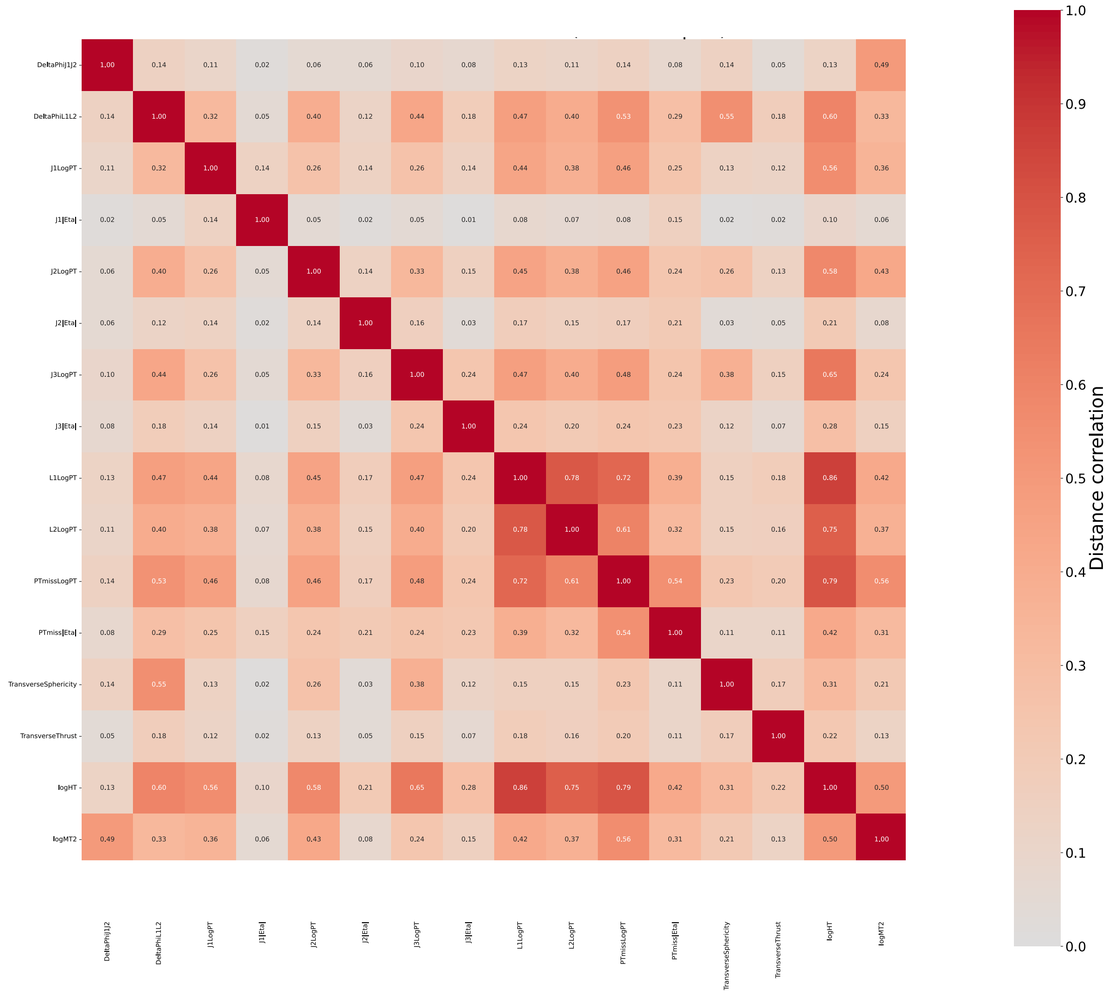


Once we have trained the flow, we can reverse its direction to transform initial correlated variables into new approximately uncorrelated ones.

Overview of the method

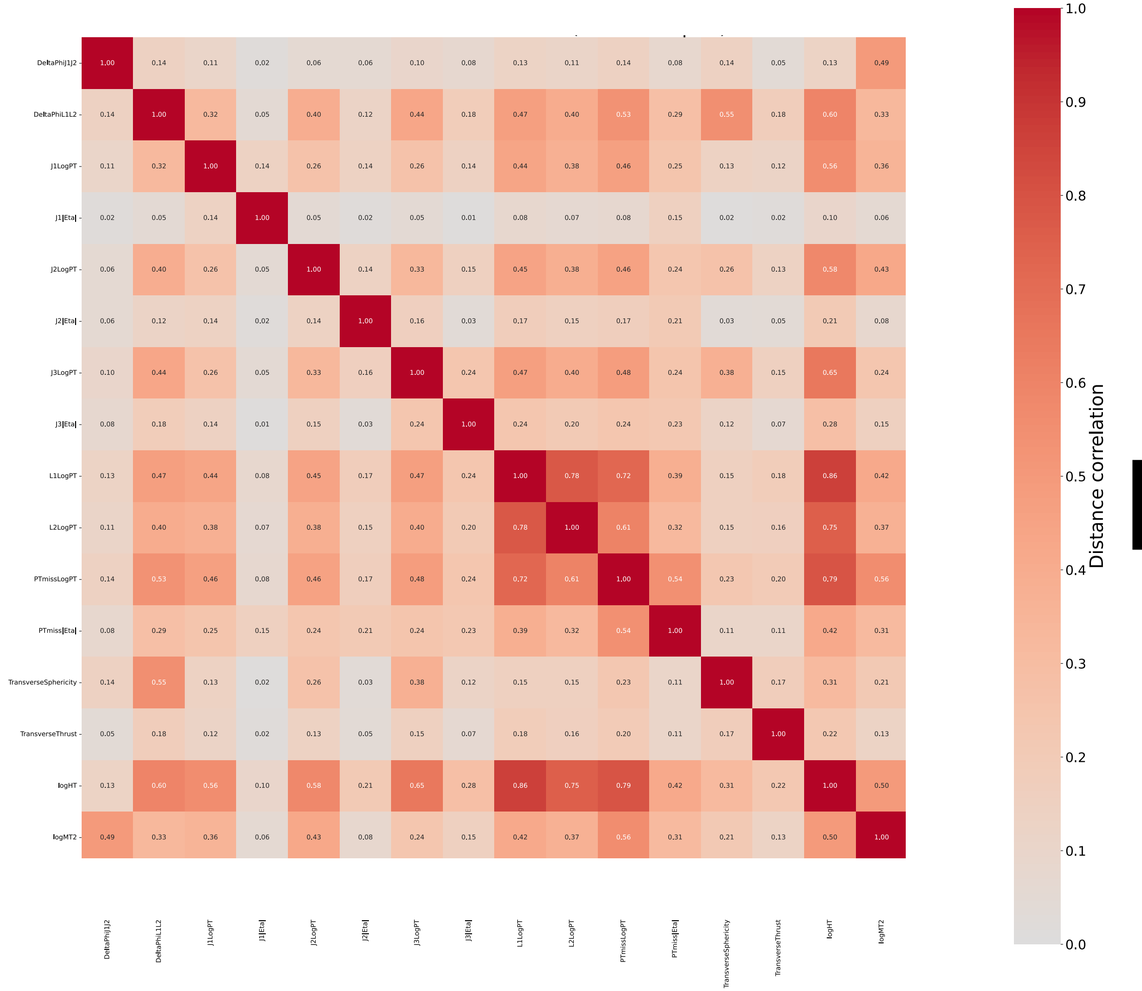


Decorrelation in practice

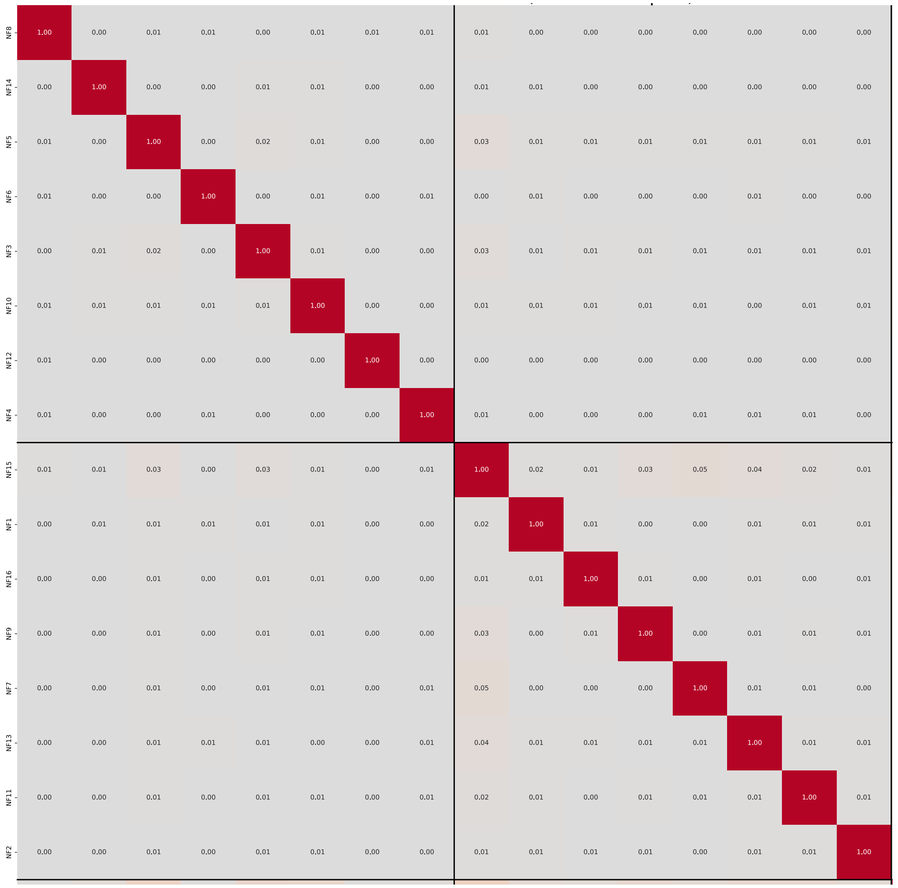


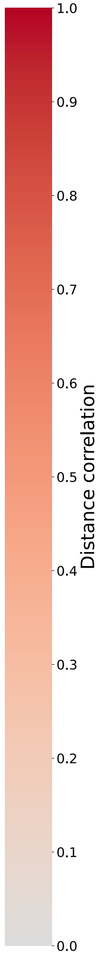
16 highly correlated variables

Decorrelation in practice



decorrelation

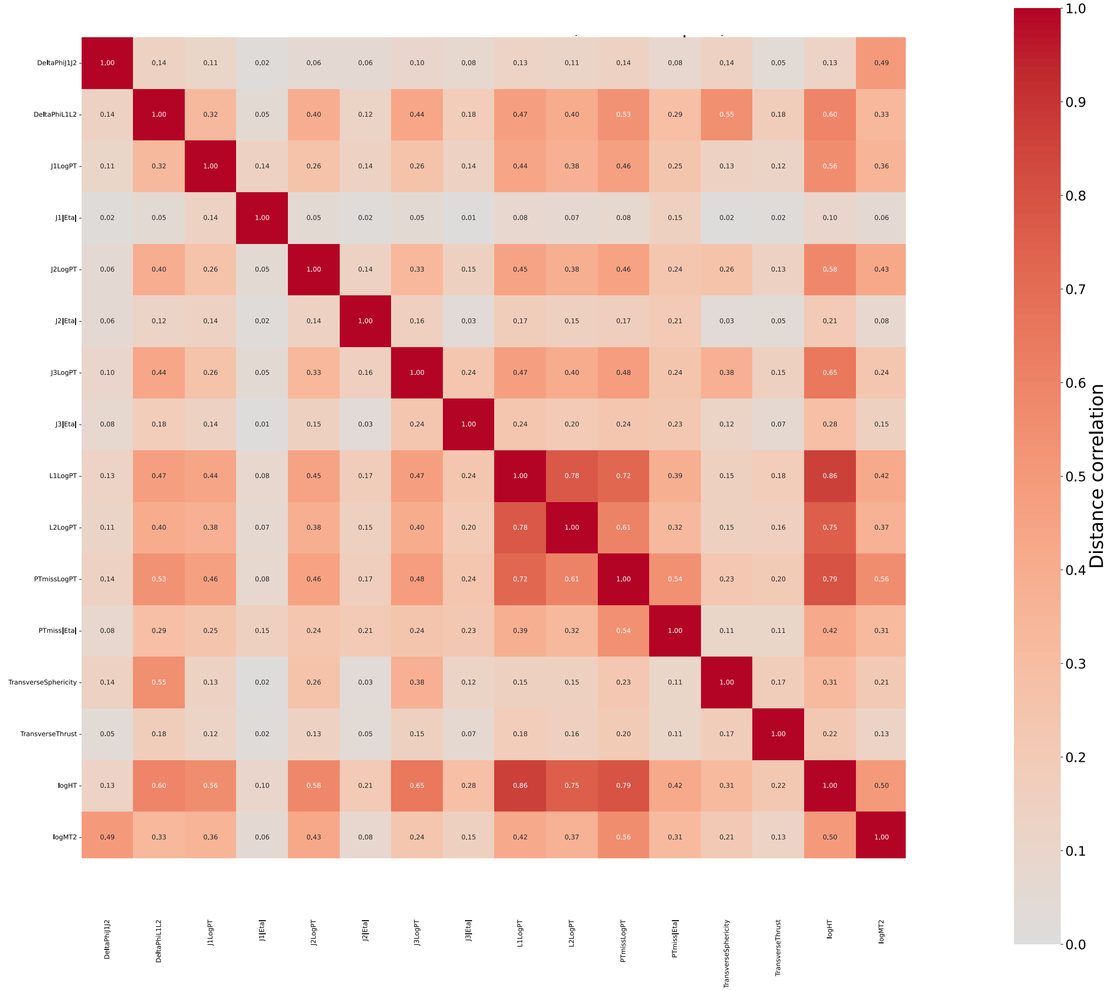




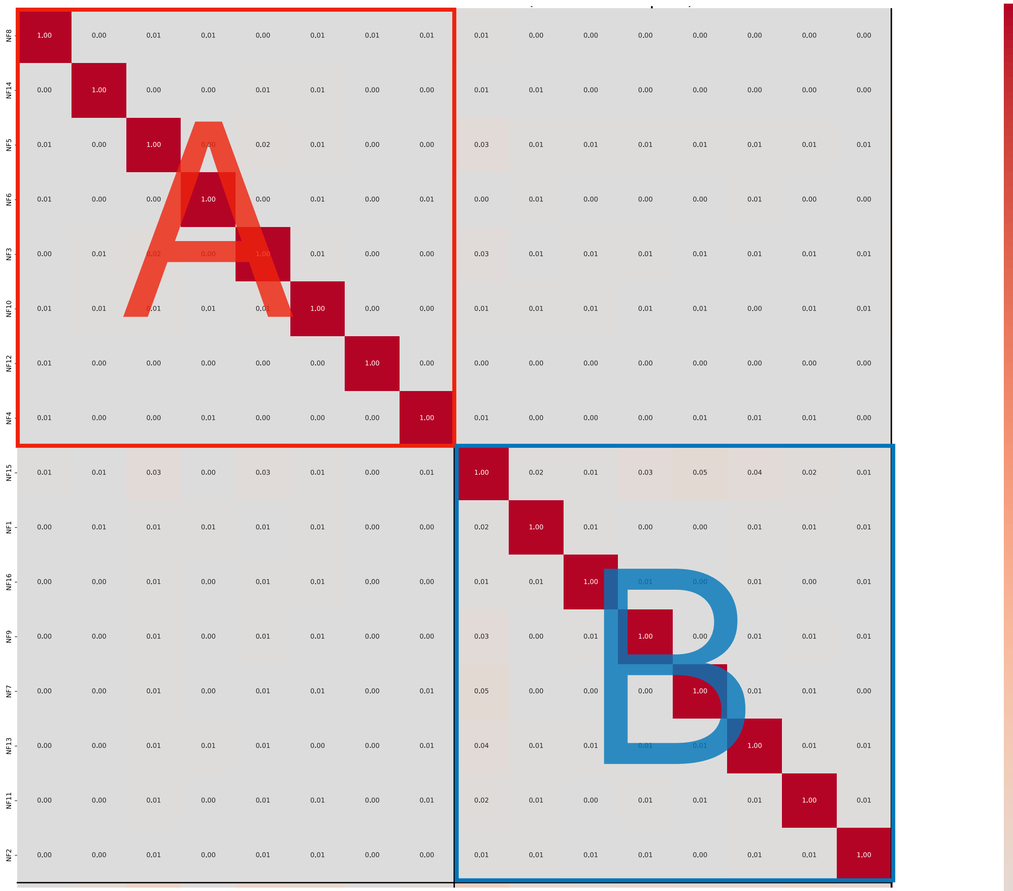
16 highly correlated variables

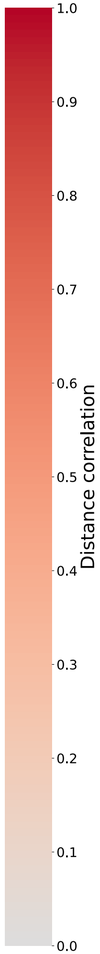
16 highly largely uncorrelated variables split into two subsets

Decorrelation in practice



decorrelation





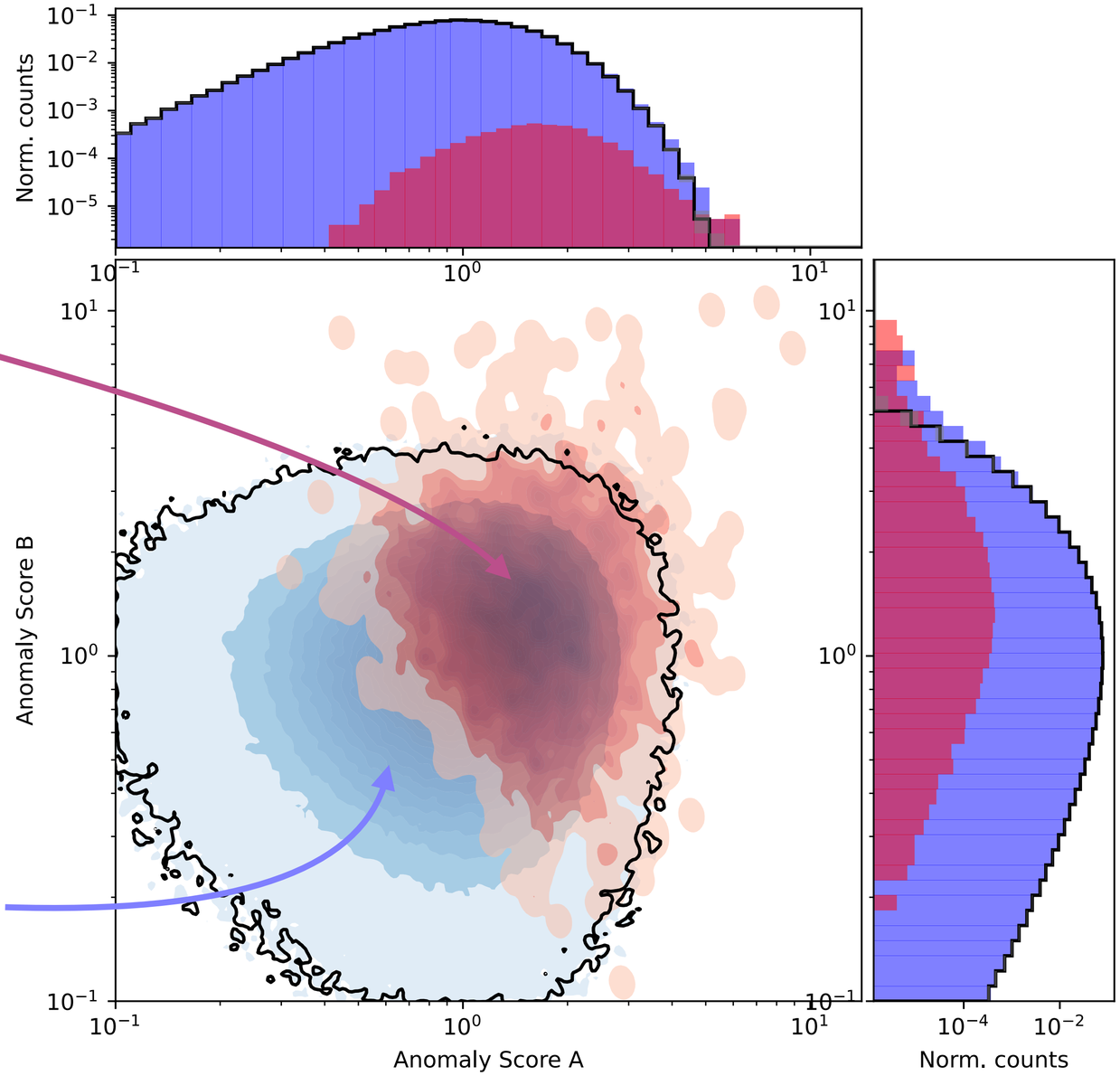
16 highly correlated variables

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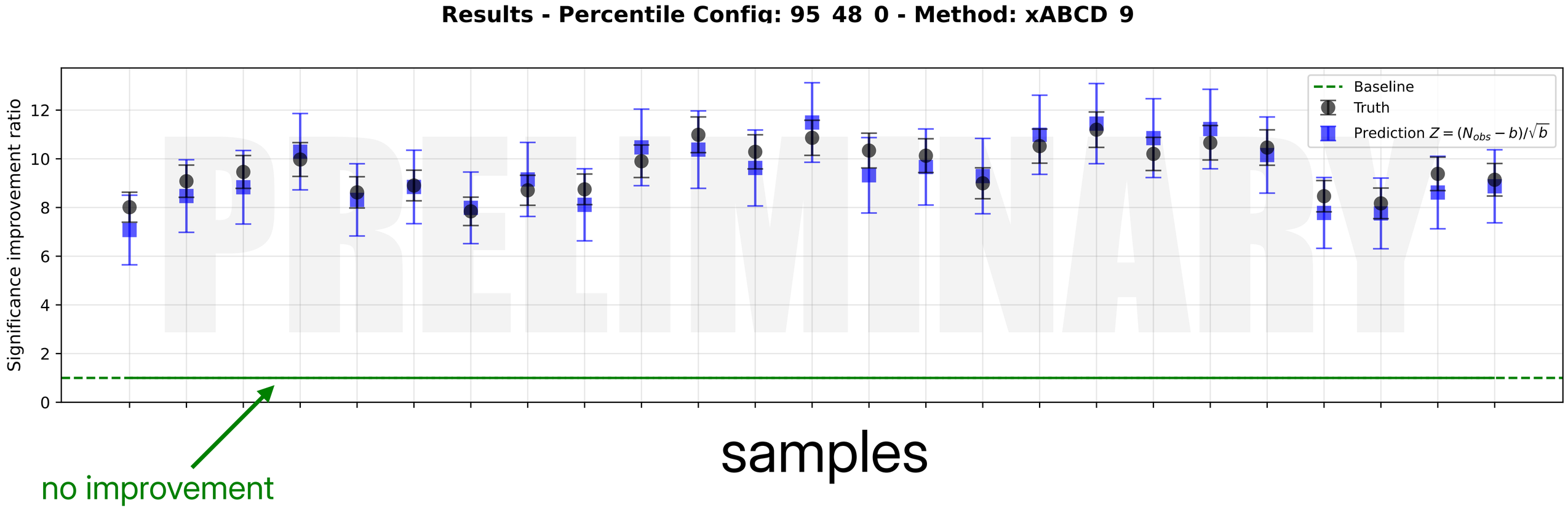
Anomaly score distribution

new physics signal

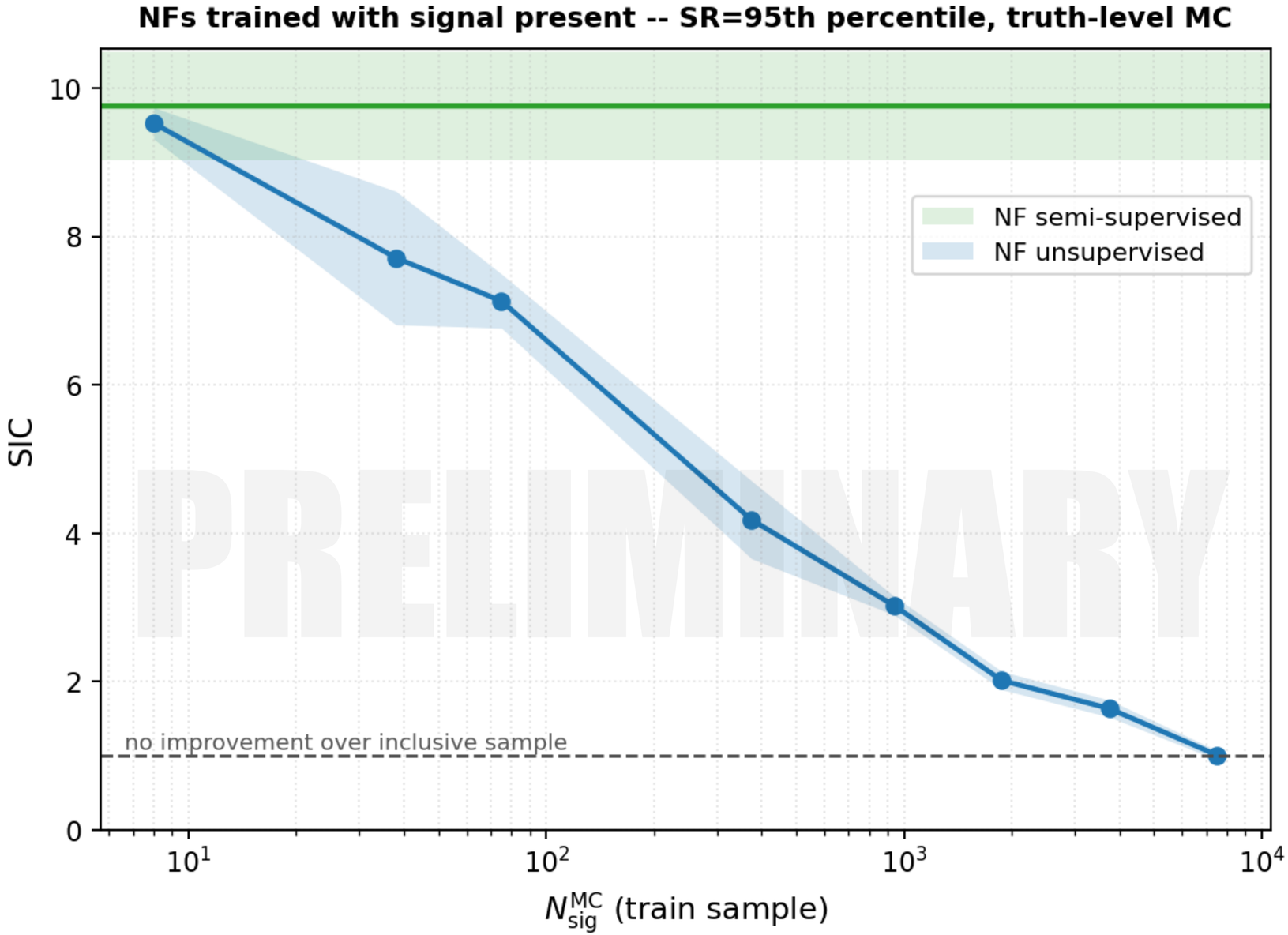
Standard Model background



Significance improvement (semi-supervised)



Towards unsupervised



Summary & Outlook

- Model-independent methods allow for broad searches for new physics
- Out-of-distribution anomaly searches are challenging:
  - general anomaly score
  - estimation of background in the signal region
- **Our approach addresses these problems by combining NFs with the ABCD matrix method**
- Preliminary results are promising
- Next steps are:
  - improve a fully unsupervised approach
  - test on other signals



Thank you for attention!

rafal.maselek@ijs.si

Mazury, Poland

BACKUP

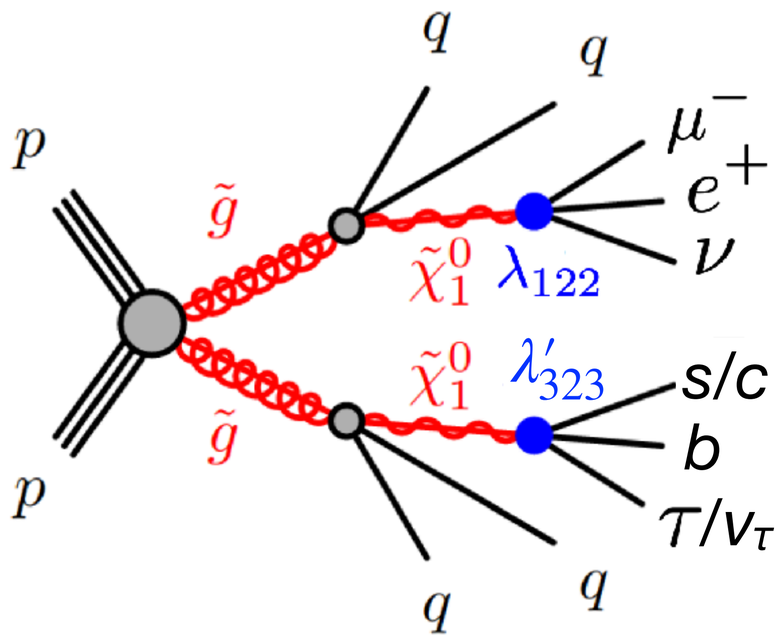
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Benchmark model

signal — RPV SUSY

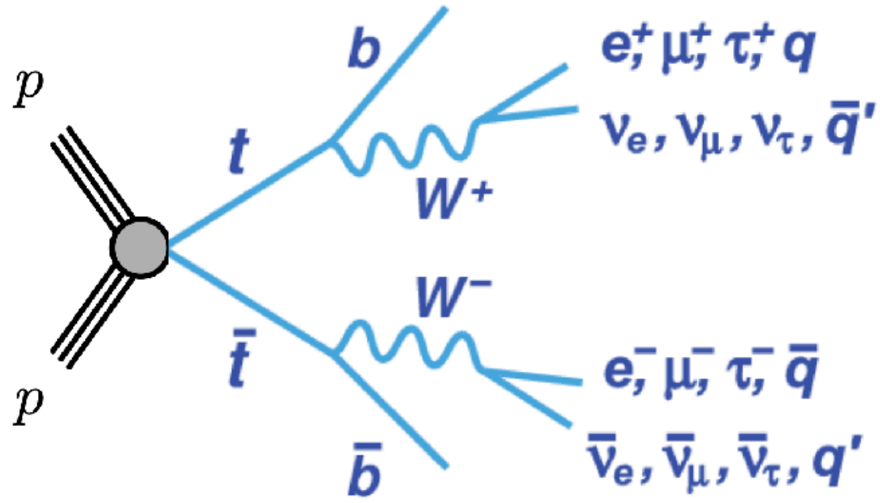


$$\mathscr{L} \ni \frac{1}{2}\lambda^{ijk} L_i L_j \bar{e}_k + \lambda^{'ijk} L_i Q_j \bar{d}_k$$

$$\lambda_{122} \simeq \lambda_{323} \neq 0$$

$$m_{\tilde{g}} = 1.8 \text{ TeV}$$
$$m_{\tilde{\chi}_1^0} = 1.7 \text{ TeV}$$

background — ttbar



Preselection & 16 original variables

Table 1: Data preselection cuts

#	Description
1	$N_{jets} \geq 3$
2	$N_{b-jets} \geq 1$
3	$N_{leptons} = 2$
4	opposite sign leptons
5	$p_T^{j1} > 60$ GeV
6	$p_T^{j2} > 30$ GeV
7	$p_T^{j3} > 30$ GeV
8	$\not{E}_T > 60$ GeV
9	$p_T^{l1} > 120$ GeV
10	$p_T^{l2} > 120$ GeV

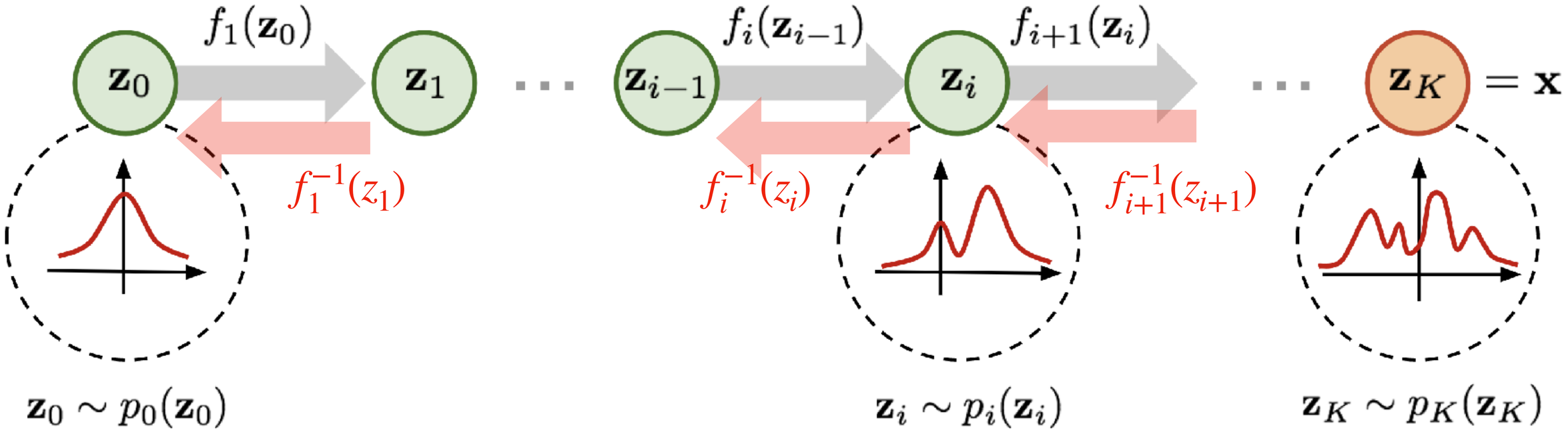
#	Name
1	$\log p_T^{j1}$
2	$\log p_T^{j2}$
3	$\log p_T^{j3}$
4	$\log p_T^{l1}$
5	$\log p_T^{l2}$
6	$\log p_T^{miss}$
7	$\log H_T$
8	$\log M_{T2}$
9	$\lvert\eta^{j1}\rvert$
10	$\lvert\eta^{j2}\rvert$
11	$\lvert\eta^{j3}\rvert$
12	$\lvert\eta^{miss}\rvert$
13	$\Delta\phi(j_1, j_2)$
14	$\Delta\phi(l_1, l_2)$
15	$T_\perp$
16	S_T

L=3/ab

S = 432 S/B = 0.5%

B = 80100 S/√B = 1.5

Normalizing Flows



$$z_K = f_\theta(z_0) = f_K \circ \ldots \circ f_2 \circ f_1(z_0) \qquad \log p_K(x) = \log p_0(z_0) + \sum_{i=1}^{K} \log \left| det \left(\frac{\partial f_{\theta,i}}{\partial z_i} \right) \right|$$

$$\mathscr{L} = \mathscr{D}_{\mathrm{KL}}\left(p_{\mathrm{data}} \,||\, p_K\right) = \int p_{\mathrm{data}} \cdot \log \left(\frac{p_{\mathrm{data}}}{p_K} \right) dx$$

optimize network parameters to minimize KL divergence

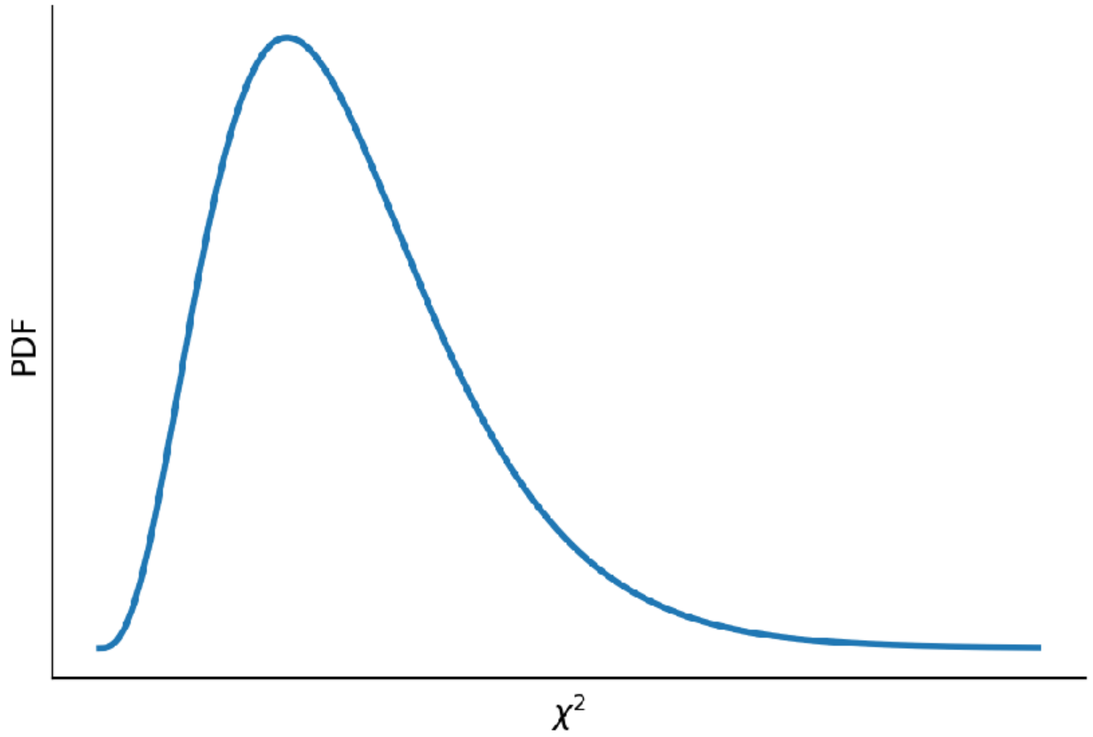
Anomaly score

anomaly scores

$$\mathscr{A}_A = \frac{1}{N_A} \sum_{z_i \in A} z_i^2$$ ← latent variables

$$\mathscr{A}_B = \frac{1}{N_B} \sum_{z_i \in B} z_i^2$$

$$\mathscr{A} = \frac{1}{N} \sum_{i=1}^{N} z_i^2 = -\frac{2}{N} \log N(0,\mathrm{I}) - \log(2\pi)$$



$$\forall_{i,j} \left(z_i \sim N(0,1)\right) \wedge \left(z_i \perp\!\!\!\perp z_j\right) \implies \mathscr{A}_{A/B} \sim \chi^2(N_A/N_B) \wedge \left(\mathscr{A}_A \perp\!\!\!\perp \mathscr{A}_B\right)$$

Training strategy

- We randomly split the data 50-25-25 (train-val-test)
- We train a normalising flow on background-only data
- We randomly split the latent variables into two subsets and construct anomaly scores A and B
- We evaluate on background + BSM signal
- We repeat for 5×5 times

